

Computational Biology and High Performance Computing

Tutorial M4 p.m.

November 6, 2000 SC'2000, Dallas, Texas



Tutorial Outline



- 8:30 a.m. 12:00 p.m.
 - Introduction to Biology
 - Overview Computational Biology
 - DNA sequences
- 1:30 p.m. 5:00 p.m.
 - Protein Sequences
 - Phylogeny
 - Specialized Databases



Tutorial Outline: Afternoon



■ 1:30 p.m. - 2:00 p.m. Working with Proteins

■ 2:00 p.m. - 3:00 p.m. Phylogeny

■ 3:00 p.m. - 3:30 p.m. BREAK

■ 3:30 p.m. - 4:30 p.m. Specialized Databases

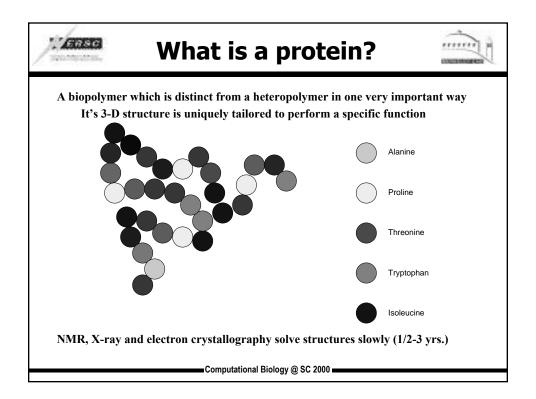
■ 4:30 p.m. - 5:00 p.m. Genetic Networks

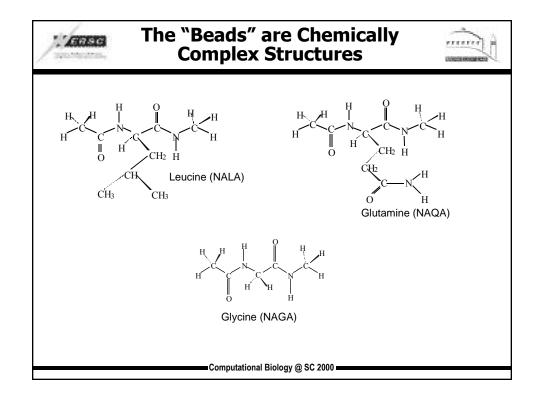
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Proteins

Manfred Zorn MDZorn@lbl.gov NERSC

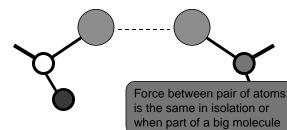






Forces Between Atoms





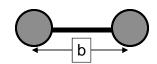
- **■** Basic assumptions:
 - ✓ Energy contributions are strictly additive
 - ✓ Energy is independent of neighbors; transferability
 - ${m
 u}$ Quantum mechanics is insignificant as long as no bonds are broken

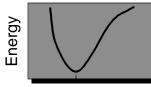
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: General

Bond Stretching Forces





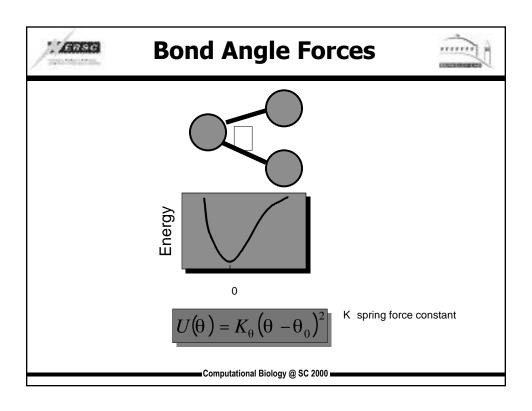


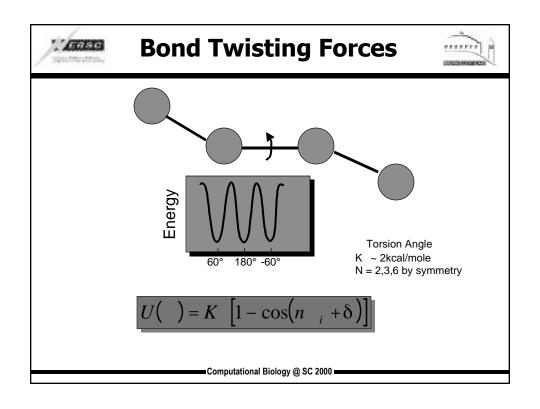
 b_0

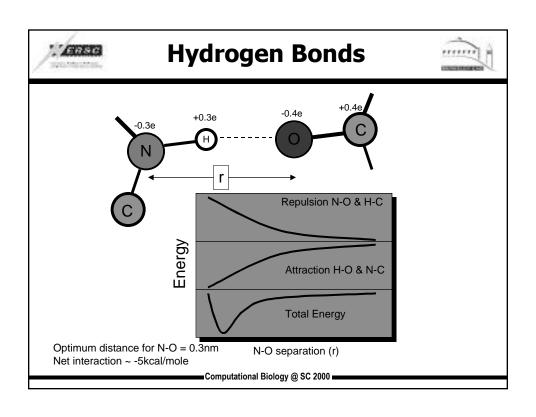
Equilibrium length ~ 0.1-0.2nm

$$U(b) = K_b (b - b_0)^2$$

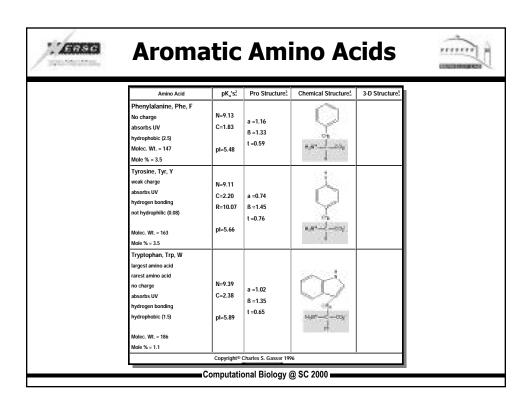
 K_b spring force constant ~ 500kcal/mole \mathring{A}^2

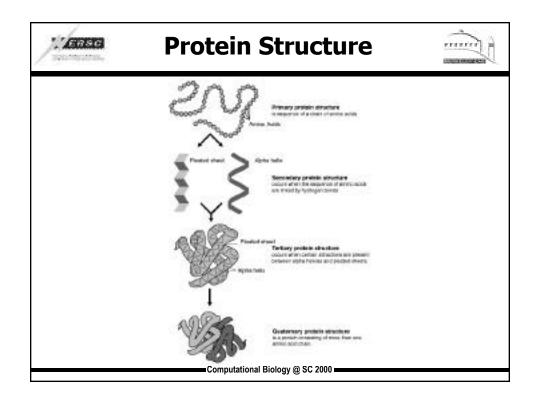


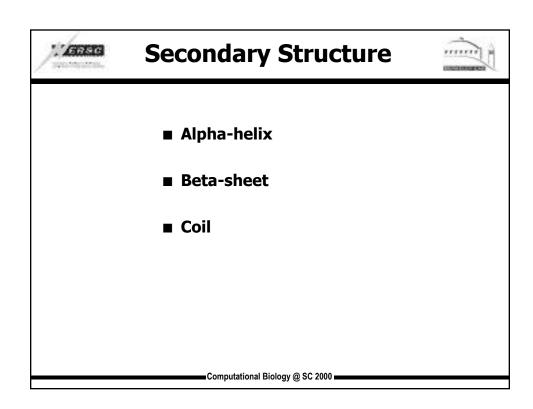


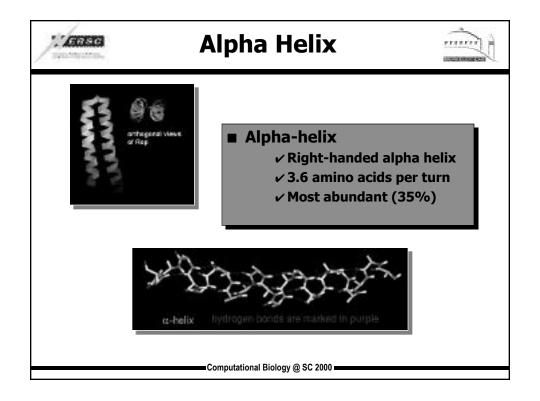


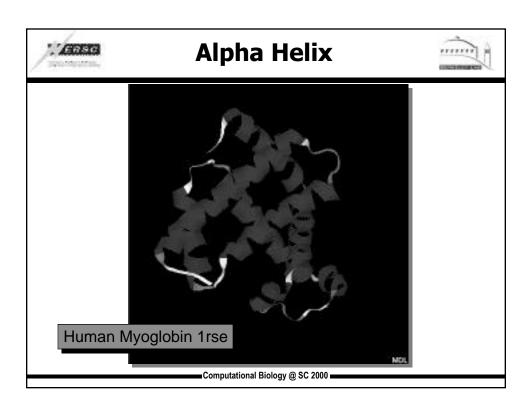
Interaction	Energy
Van der Waals (in water)	(kcal/mole) -0.1
	.
Hydrogen bond (in water)	-1.0
Torsion barrier (single bond)	~+3.0
Torsion barrier (double bond	+20.0
Bond breakage	+100.0
Change bond angle by 10°	+2.0
Stretch bond length by 10p	m (0.1Å) +2.5
Thermal energy 300K	0.6

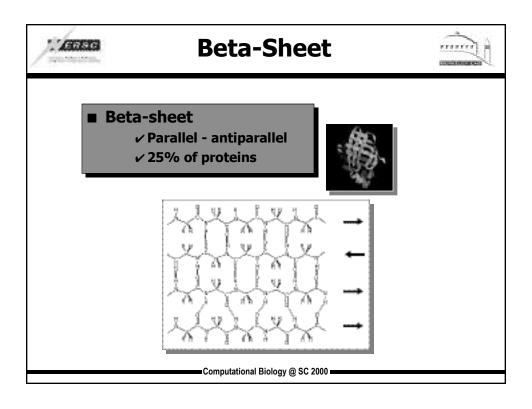


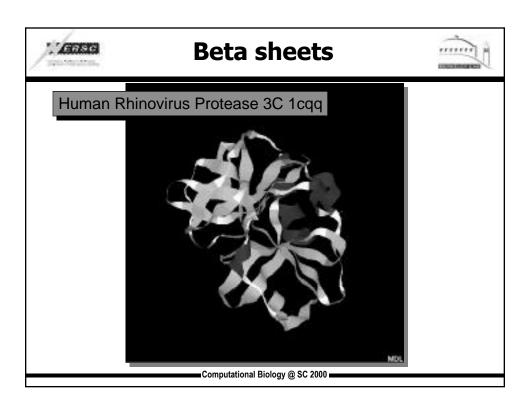














SCOP: Structural Classification of Proteins



- 1. All alpha proteins (a)
- 2. All beta proteins (b)
- 3. Alpha and beta proteins (a/b)
 - ✓ Mainly parallel beta sheets (beta-alpha-beta units)
- 4. Alpha and beta proteins (a+b)
 - ${m
 u}$ Mainly antiparallel beta sheets (segregated alpha and beta regions)
- 5. Multi-domain proteins (alpha and beta)
 - arksigma Folds consisting of two or more domains belonging to different classes
- 6. Membrane and cell surface proteins and peptides
 - $\boldsymbol{\boldsymbol{\nu}}$ Does not include proteins in the immune system
- 7. Small proteins
 - ✓ Usually dominated by metal ligand, heme, and/or disulfide bridges
- 8. Coiled coil proteins
- 9. Low resolution protein structures
- 10. Peptides
- 11. Designed proteins



SCOP Classifications



128	197	
	197	296
87	158	251
93	153	323
168	237	345
25	25	32
11	17	19
52	72	102
564	859	1368
	93 168 25 11 52	93 153 168 237 25 25 11 17 52 72

11410 PDB Entries (1 Jul 2000).

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Protein Fold Recognition, Structure Prediction, and Folding



- Drawing analogies with known protein structures
 - ✓ Sequence homology, Structural Homology
 - ✓ Inverse Folding, Threading
- Ab initio folding: the ability to follow kinetics, mechanism
 - ✓ robust objective function
 - ✓ severe time-scale problem
 - ${m arepsilon}$ proper treatment of long-ranged interactions
- Ab initio prediction: the ability to extrapolate to unknown folds
 - ✓ multiple minima problem
 - ✓ robust objective function
 - ✓ Stochastic Perturbation and Soft Constraints
- Simplified Models that Capture the Essence of Real Proteins
 - ✓ Lattice and Off-Lattice Simulations
 - ✓ Off-Lattice Model that Connect to Experiments: Whole Genomes?



Protein Fold Predictions: Neural Network Structure Classifications



- Protein fold predictor based on global descriptors of amino acid sequence
- Empirical prediction using a database of known folds in machine learning
- Databases
 - 3D-ALI (83 folds)
 - SCOP (used ~120 folds)
- Representation of protein sequence in terms of physical, chemical, and structural properties of amino acids
- Feed forward neural network for machine learning

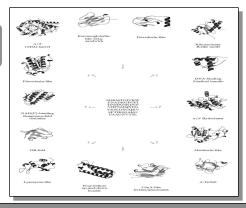
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Protein Fold Recognition: Threading



Sequence Assignments to Protein Fold Topology (David Eisenberg, UCLA)



Take a sequence with unknown structure and align onto structural template of a given fold Score how compatible that sequence is based on empirical knowledge of protein structure Right now 25-30% of new sequences can be assigned with high confidence to fold class 100,000's of sequences and 10,000's of structures (each of order 10²-10³ amino acids long)



Protein Fold Recognition: Threading



Computational Approach:

 $\label{eq:Dynamic programming: capable of finding optimal alignments if optimal alignments of subsequences can be extended to optimal alignments of whole objective functions that are one-dimensional E= <math>V_i + V_{gap}$

Complexity: all to all comparison of sequence to structure scales as L^2 Whole human genome: 10^{13} flops

Improve Objective function:

Take into account structural environment

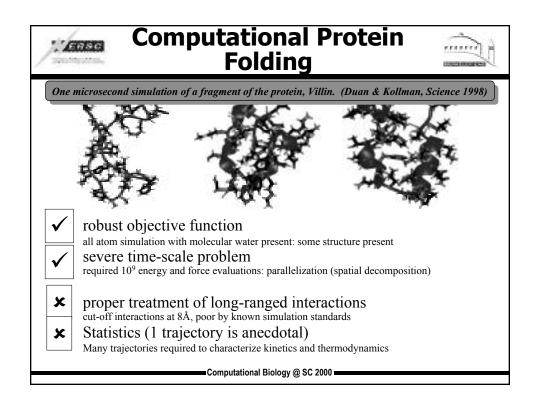
3D ED: dynamic programming, L2

Build pairwise or multi-body objective function

NP-hard if: variable-length gaps and model nonlocal effects such as distance dependence

Recursive dynamic programming, Hidden markov models, stochastic grammers

Complexity: all to all comparison of sequence to structure scales as L^3 Whole human genome: ${\sim}10^{16}$ flops





Computational Protein Folding



- (1) Size-scaling bottlenecks: Depends on complexity of energy function, V
- Empirical (less accurate): cN2; ab initio (more accurate): CN3 or worse; c<<C
- empirical force field used
- "long-ranged interactions" truncated so cM^2 scaling; $M \le N$
- spatial decomposition, linked lists
- (2) Time-Scale of motions bottlenecks (Δt)

$$r_{i}(t+t) = 2r_{i}(t) - r_{i}(t-t) + \frac{f_{i}(t)}{m_{i}} \frac{(t)^{2}}{2!} + O[(t)^{4}]; v_{i}(t) = \frac{r_{i}(t+t) - r_{i}(t-t)}{2t} + O[(t)^{3}]$$

$$f_{i} = m_{i}a_{i} = -\frac{1}{i}V(r_{1}, r_{2}, \dots r_{N})$$

Use timestep commensurate with fastest timescale in your system

bond vibrations: 0.01Å amplitude: 10-15 seconds (1fs)

Shake/Rattle bonds (2fs)

Multiple timescale algorithms (~5fs) (not used here)

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Ab Initio **Protein Structure Prediction**



Primary Squence and an Energy function → Tertiary structure

Empirical energy functions:

(1) Detailed, Atomic description: leads to enormous difficulties!

$$V_{MM} = \int_{i}^{\# Bonds} \left(b_{i} - b_{o}\right)^{2} + \int_{i}^{\# Angles} \left(\theta_{i} - \theta_{o}\right)^{2} + \int_{i}^{\# Impropers} \left(\tau_{i} - \tau_{o}\right)^{2} + \int_{i}^{\# Impropers$$

(1) Multiple minima problem is fierce

Find a way to effectively overcome the multiple minima problem

(2) Objective Functions: Replaceable algorithmic component?

Global energy minimum should be native structure, misfolds higher in energy



The Objective (Energy) **Function**



Empirical Protein Force Fields: AMBER, CHARMM, ECEPP "gas phase"





CATH protein classification: http://pdb.pdb.bnl.gov/bsm/cath

 α -helical sequence/ β -sheet structure

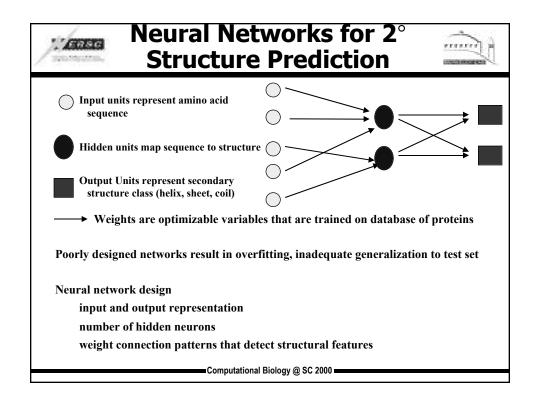
β-sheet sequence/a-helical structure

Energies the same! Makes energy minimization difficult!

Add penalty for exposing hydrophobic surface: favors more compact structures

 $E_{native \ folds} < E_{misfolds}$ for a few test cases

Solvent accessible surface area functions: Numerically difficult to use in optimization





Neural Network Results



No sequence homology through multiple alignments

Train

Test

Total predicted correctly = 66%

Total predicted correctly = 62.5%

Helix: 51% $C_a=0.42$ Sheet: 38% $C_b=0.39$ Helix: 48% $C_a=0.38$ Sheet: 28% $C_b=0.31$

Coil: 82% $C_c = 0.36$

Coil: 84% $C_c = 0.35$

Network with Design: Yu and Head-Gordon, Phys. Rev. E 1995

Train

Test

Total predicted correctly = 67%

Total predicted correctly = 66.5%

Helix: 66% $C_a = 0.52$

Helix: 64% $C_a=0.48$

Sheet: 63% C_b=0.46

Sheet: 53% $C_b = 0.43$

Coil: 69% C_c=0.43

Coil: 73% C_c =0.44

Combine networks of Yu and Head-Gordon with multiple alignments

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Neural Networks Used To Guide Global Optimization Methods



Generate expanded tree of configurations

Predicted coil residues: generate random, dissimilar sets of $_0$ and $_0$

Explore tree configuration in depth:

Global Optimization in sub-space of coil residues: walk through barriers, move downhill

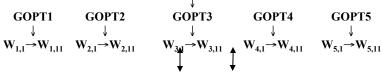


Hierarchical Parallel Implementation of Global Optimization Algorithm



Static vs. Dynamic Load Balancing of Tasks





Central Processor: Assigns starting coordinates to GOPT's

Task time is highly variable

GOPT's: Divide up sub-space into N regions for global search

Task time is variable

Workers: Generate sample points; find best minimizer in region (Number of workers depends on sub-space)

Dynamical load balancing of tasks: reassigning GOPT/workers to GOPT/workers

Gain in efficiency of a factor of 5-10

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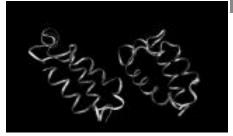




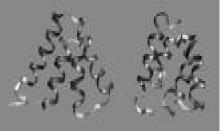
Crystal (left), Prediction (right) R.M.S. 7.0Å



1pou: 72 aa DNA binding protein



2utg A: 70aa -chain of uteroglobin:



Prediction (left) and crystal (right) R.M.S. 6.3Å

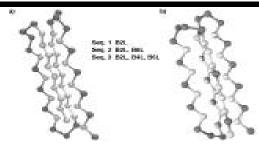


Still have not reached crystal energy yet!



Simplified Models for Simulating Protein Folding





Simplifies the "real" energy surface topology sufficiently that you can do

- (1) Statistics ✓
 - Can do many trajectories to converge kinetics and thermodynamics
- (2) severe time-scale problem✓
 - characterize full folding pathway: mechanism, kinetics, thermodynamics
- (3) proper treatment of long-ranged interactions ✓ all interactions are evaluated; no explicit electrostatics
- (4) robust objective function? good comparison to experiments

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Greg Hura, Graduate Group in Biophysics, UCB

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Robert M. Glaeser, Mol. & Cell Biology, UCB and Life Sciences Division, LBNL

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Structure-Based Drug Discovery

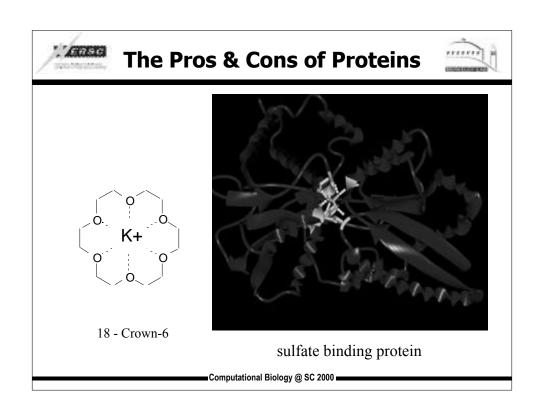
Brian K. Shoichet, Ph.D Northwestern University, Dept of MPBC 303 E. Chicago Ave, Chicago, IL 60611-3008 Nov 15, 1999

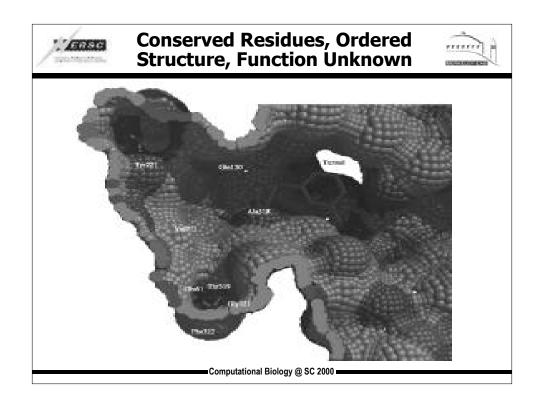


Problems in Structure-Based Inhibitor Discovery & Design



- **■** Balance of forces in binding
 - Energies in condensed phases
 - ✓ interaction energies
 - ✓ desolvation
- **■** Problem scales badly with degrees of freedom
 - Configuration
 - √ configs = (prot-features)⁴ X (lig-features)⁴
 - Conformation
 - ∠ Ligand & Protein, confs = 3lbonds X 3pbonds
- Sampling chemical space (scales very badly)
- **■** Defining binding sites







Inhibitor Discovery or Design?

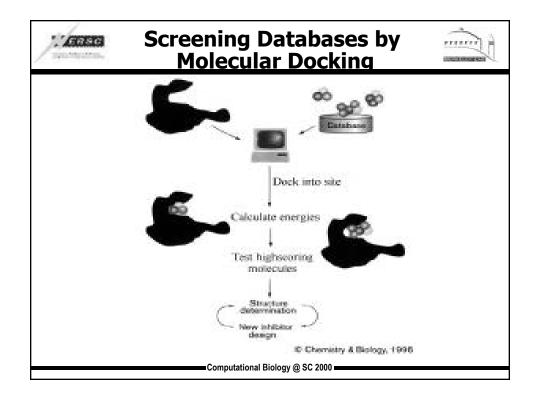


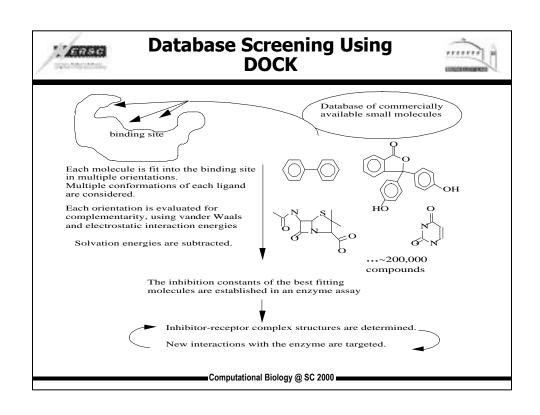
■ Design ligands

- Ludi (Bohm)
- Grow (Moon & Howe)
- Builder (Roe & Kuntz)
- MCSS-Hook (Miranker & Karplus)
- SMOG (DeWitte & Shaknovitch)
- Others...

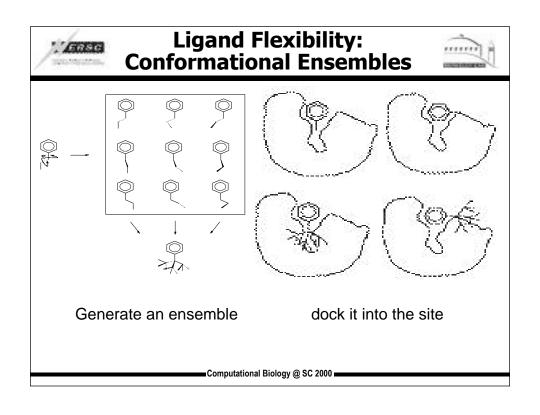
■ Discover Ligands

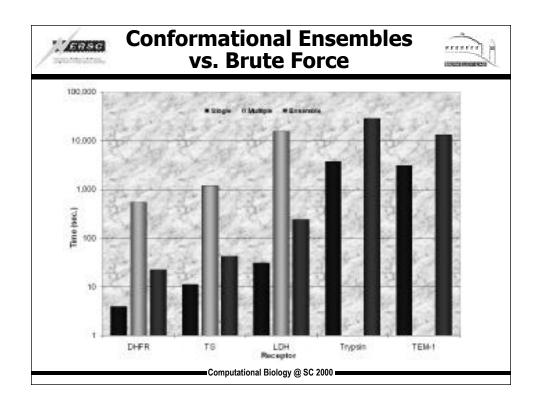
- DOCK (Kuntz, et al., Shoichet)
- CAVEAT (Bartlett)
- Monte Carlo (Hart & Read)
- AutoDock (Goodsell & Olson)
- SPECITOPE (Kuhn et al)
- Others...





Novel Ligand Discovery Using Molecular Docking . GEER Lead from Lead from molecular docking Receptor molecular docking HIV HGXPRTase protease thymidylate synthase hemagglutinin -lactamase cercarial elastase malarial protease -lactamase thymidylate CD4-gp120 unpublished synthase ■Computational Biology @ SC 2000 ■

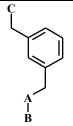






Hierarchical Docking





Flexible docking:

Hierarchical docking:

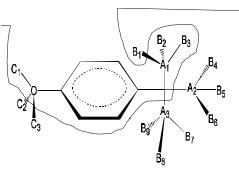
27 confs

27 confs

x3 atoms

81 atom positions

 $\frac{3C + 3A + 9B}{15 \text{ atom positions}}$





Computational Phylogenetics

Craig Stewart stewart@iu.edu Indiana University



Outline



- **■** Evolution & Phylogenetics
- Why is this an HPC problem?
- Alignment (brief)
- Summary of methods and software for phylogenetics
- One example in detail: Maximum Likelihood analysis with fastDNAml
- Some interesting results and challenges for the future
- Caveat: this is an introduction, not an exhaustive review.



Phylogeny



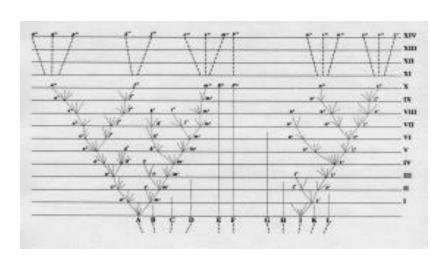
- Evolution is an explicitly historical branch of biology, one in which the subjects are active players in the historical changes.
- A phylogeny, or phylogenetic tree, is a way of depicting evolutionary relationships among organisms, genes, or gene products.
- Modern evolutionary theory began with Darwin's Origin of Species, which included one figure an evolutionary tree

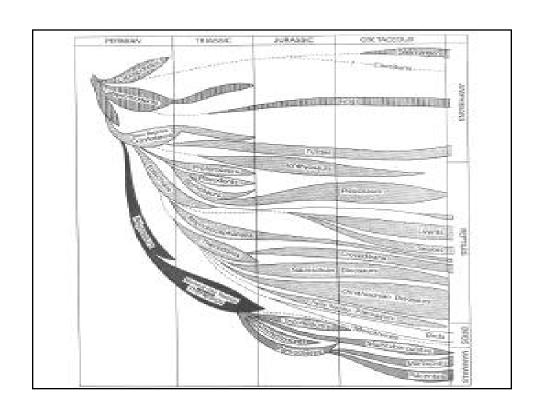
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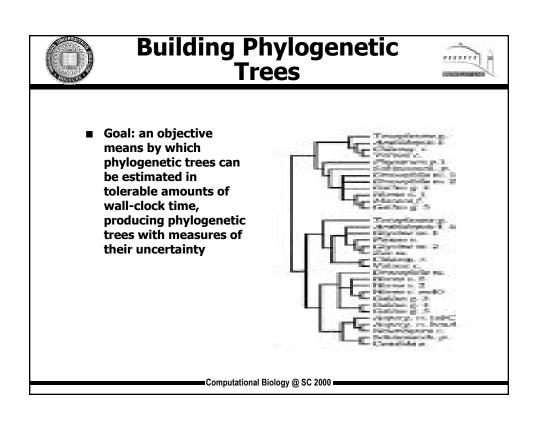


Origin of Species, Figure 1







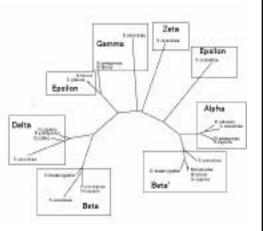




Basic Evolutionary Biology



- All evolutionary changes are described as bifurcating trees
 - evolutionary relationships amongenes or gene products (trees of paralogues)
 - evolutionary relationships amonorganisms (trees of orthologues)



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Why?



- Curiosity: Anyone who as a child wandered through the dinosaur section of a natural history museum understands the inherent intellectual attraction of evolutionary biology
- Theoretical uses: testing hypotheses in evolutionary biology
- Practical uses:
 - Medicine
 - Environmental management (biodiversity maintenance)



Reconstructing history from DNA sequences



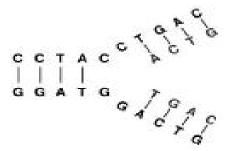
- DNA changes over time; much of this change is not expressed
- Changes in unexpressed DNA can be modeled as Markov processes
- By comparing similar regions of DNA from different organisms (or different genes) one can infer the phylogenetic tree and evolutionary history that seems the best explanation of the current situation

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DNA replication





Purines: Pyrimidines:

Adenine & Guanine Thymine & Cytosine



Changes in genetic information over time



■ Point mutations

DNA – sequences of the 4 nucleotides

CCTCTGAC

vs

TCTCCGAC

Protein - sequences of the 20 amino acids

GSAQVKGHGKK

vs

GNPKVKAHGKK

■ Insertions and deletions

DNA

CCTCT+GAC

vs

CCTCTTGAC

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Sequences available

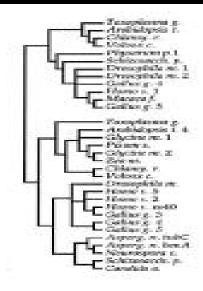


- DNA (sequences are series of the base molecules; aligned sequences will also contain +s for gaps)
- Amino acid sequences (series of letters indicating the 20 amino acids). Computational challenges more severe than with DNA sequences.
- RNA
- The availability of data at present exceeds the ability of researchers to analyze it!



Why is tree-building a HPC problem?





- The number of bifurcating unrooted trees for n taxa is (2n-5)!/ (n-3)! 2n-3
- for 50 taxa the number of possible trees is ~1074; most scientists are interested in much larger problems
- The number of rooted trees is (2n-5)!

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Alignment



- To build trees one compares and relates 'similar' segments of genetic data. Getting 'similar' right is absolutely critical!
- Methods:
 - dynamic programming
 - Hidden Markov Models
 - Pattern matching
- Some alignment packages:
 - BLAST
 http://www.ncbi.nlm.nih.gov/BLAST/
 - FASTA http://gcg.nhri.org.tw/fasta.html
 - MUSCA http://www.research.ibm.com/bioinformatics/home



Matching cost function



GCTAAATTC

++ x x

GC AAGTT

- Penalize for mismatches, for opening of gap, and for gap length
- This approach assumes independence of loci: good assumption for DNA, some problems with respect to amino acids, significant problems with RNA

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Example of aligned sequences



Thermotoga ATTTGCCCCA GAAATTAAAG CAAAAACCCC AGTAAGTTGG GGATGGCAAA Tthermophi ATTTGCCCCA GGGGTTCCCG CAAAAACCCC AGTAAGTTGG GGATGGCAGG Taquaticus ATTTGCCCCA GGGGTTCCCG CAAAAACCCC AGTAAGTTGG GGATGGCAGG G deinon ATTTGCCCCA GGGATTCCCG CAAAAACCCC AGTAAGTTGG GGATGGCAGG G Chlamydi ATTTTCCCCA GAAATTCCCG AAAAAACCCC AATAAATTGG GGATGGCAGG flexistips ATTTTCCCCA CAAAAAAAA AAAAAACCCC AGTAAGTTGG GGATGGCAGG borrelia-b ATTTGCCCCA GAAGTTAAAG CAAAAACCCC AATAAGTTGG GGATGGCAGG bacteroide ATTTGCCCCA GAAATTCCCG CAAAAACCCC AGTAAATTGG GGATGGCAGG GG Pseudom ATTTGCCCCA GGGATTCCCG CAAAAACCCC AGTAAGTTGG GGATGGCAGG G ecoli---- GTTTTCCCCA GAAATTCCCG CAAAAACCCC AGTAAGTTGG GGATGGCAGG shewanella GTTTGCCCCA GCCATTCCCG TAAAAACCCC AGTAAGTTGG GGATGGCAGG bacillus-- ATTTGCCCCA GAAATTCCCG CAAAAACCCC AGCAAATTGG GGATGGCAGG G myco-gentl ATTTGCCCCG GAAATTCCCG CAAAAACCCC AGTAAGTTGG GGATGGCAAA



Phylogenetic methodologies



- Define a specific series of steps to produce the 'best' tree
 - Pair-group cluster analyses
 - Fast, but tend not to address underlying evolutionary mechanisms
- Define criteria for comparing different trees and judging which is better. Two steps:
 - Define the objective function (evolutionary biology)
 - Generate and compare trees (computation)
- All of the techniques described produce an unrooted tree.
- The trees produced likewise describe relationships among extant taxa, not the progress of evolution over time

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Distance-based Treebuilding methods



- Aligned sequences are compared, and analysis is based on the differences between sequences, rather than the original sequence data.
- Less computationally intensive than characterbased methods
- Tend to be problematic when sequences are highly divergent



Distance-based Tree building methods, 2



- Cluster analysis. Most common variant is Unweighted Pair Group Method with Arithmetic Mean (UPGMA) – join two closest neighbors, average pair, keep going. Problematic when highly diverged sequences are involved
- Additive tree methods built on assumption that the lengths of branches can be summed to create some measure of overall evolution.
 - Fitch-Margoliash (FM) minimizes squared deviation between observed data and inferred tree.
 - Minimum evolution (ME) finds shortest tree consistent with data
- Of the distance methods, ME is the most widely implemented in computer programs

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Character-based methods



- Use character data (actual sequences) rather than distance data
- Maximum parsimony. Creates shortest tree one with fewest changes. Inter-site rate heterogeneity creates difficulties for this approach.
- Maximum likelihood. Searches for the evolutionary model that has the highest likelihood value given the data. In simulation studies ML tends to outperform others, but is also computationally intensive.



Rooting trees



- If the assumption of a constant molecular clock holds, then the root is the midpoint of the longest span across the tree.
- Sometimes done by including an 'outgroup' in the analysis
- Remember that the trees produced from sequence data are fundamentally different than a historical evolutionary tree

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Evaluating trees



- Once a phylogenetic tree has been produced by some means, how do you test whether or not the tree represents evolutionary change, or just the results of a mathematical technique applied to a set of random data? These methods below can be used to perform a statistical significance test.
- **■** Significance tests for MP trees:
 - Skewness tests. MP tree lengths produced from random data should be symmetric; tree lengths produced from data sets with real signal should be skewed.
- Significance tests for distance, MP, and ML trees:
 - Bootstrap. Recalculate trees using multiple samples from same data with resampling.
 - Jackknife. Recalculate trees using subsampling
- All of these methods are topics of active debate



Phylogenetic software



- Phylip. (J. Felsenstein). Collection of software packages that cover most types of analysis. One of the most popular software collections. Free.
- PAUP. (D. Swofford). Parsimony, distance, and ML methods. Also one of the most popular software collections. Not free, but not expensive.
- PAML. (Ziheng Yang). Maximum likelihood methods for DNA and proteins. Not as well suited for tree searching, but performs several analyses not generally available. Free.
- fastDNAml. (G. Olsen). Maximum likelihood method for DNA; becoming one of the more popular ML packages. MPI version available soon; well suited to tree searching in large data sets. Free.

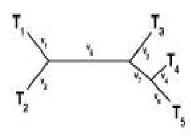
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More on Maximum Likelihood methods



- Typical statistical inference: calculate probability of data given the hypothesis
- Tree, branch lengths, and associated likelihood values all calculated from the data.
- Likelihood values used to compare trees and determine which is best





Stochastic change of DNA



Markov process, independent for each site: 4 x 4 matrix for DNA, 20 x 20 for amino acids

	A	С	G	Т
Α	p(A->A)	p(A->C)	p(A->G)	
С	p(C->A)	p(C->C)	p(C->G)	
G				
Т				

- **■** Transitions more probable than transversions.
- Must account for heterogeneity in substitution rates among sites (DNArates – Olsen)

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fastDNAml



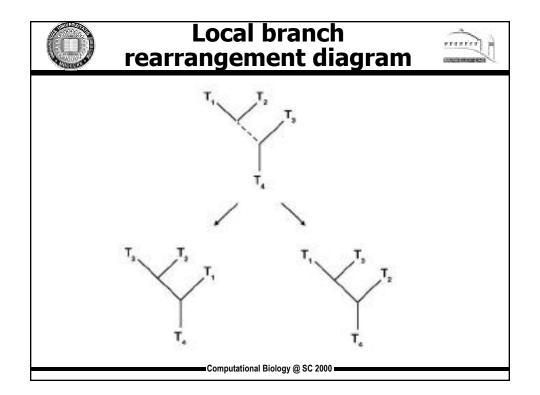
- **■** Developed by Gary Olsen
- Derived from Felsensteins's PHYLIP programs
- One of the more commonly used ML methods
- The first phylogenetic software implemented in a parallel program (at Argonne National Laboratory, using P4 libraries)
- Olsen, G.J., et al.1994. fastDNAml: a tool for construction of phylogenetic trees of DNA sequences using maximum likelihood. Computer Applications in Biosciences 10: 41-48
- MPI version produced in collaboration with Indiana University will be available soon



fastDNAml algorithm



- Compute the optimal tree for three taxa (chosen randomly) only one topology possible
- Randomly pick another taxon, and consider each of the 2i-5 trees possible by adding this taxon into the first, three-taxa tree.
- Keep the best (maximum likelihood tree)
- Local branch rearrangement: move any subtree to a neighboring branch (2i-6 possibilities)
- **■** Keep best resulting tree
- Repeat this step until local swapping no longer improves likelihood value

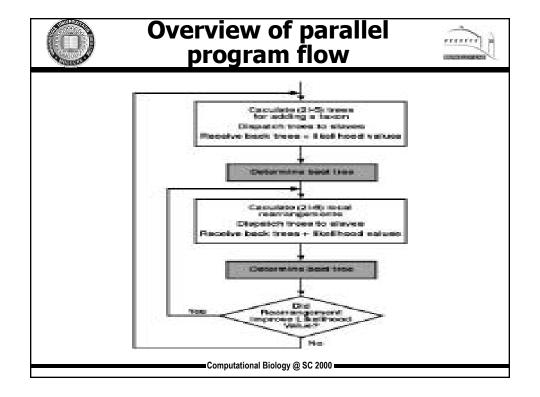




fastDNAml algorithm con't: Iterate



- Get sequence data for next taxon
- Add new taxa (2i-5)
- Keep best
- Local rearrangements (2i-6)
- Keep best
- Keep going....
- When all taxa have been added, perform a full tree check

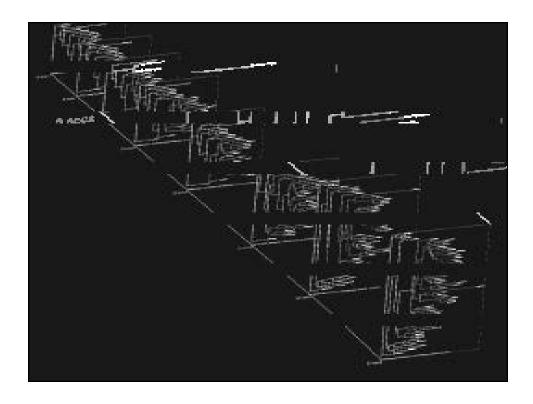


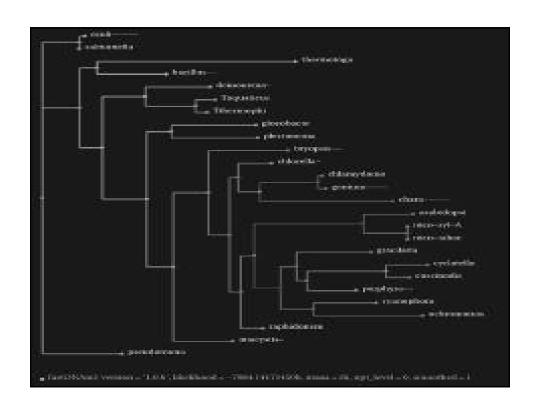


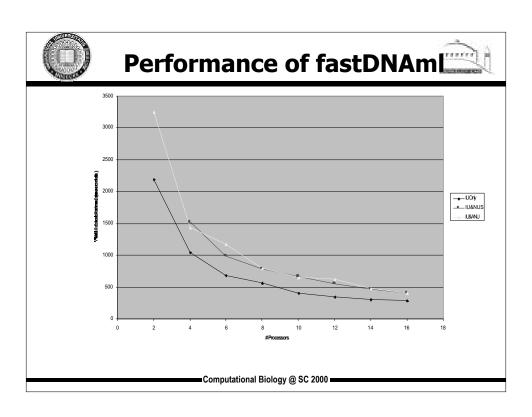
Because of local effects....



- Where you end up sometimes depends on where you start
- This process searches a huge space of possible trees, and is thus dependent upon the randomly selected initial taxa
- Can get stuck in local optimum, rather than global
- Must do multiple runs with different randomizations of taxon entry order, and compare the results
- Similar trees and likelihood values provide some confidence, but still the space of all possible trees has not been searched extensively





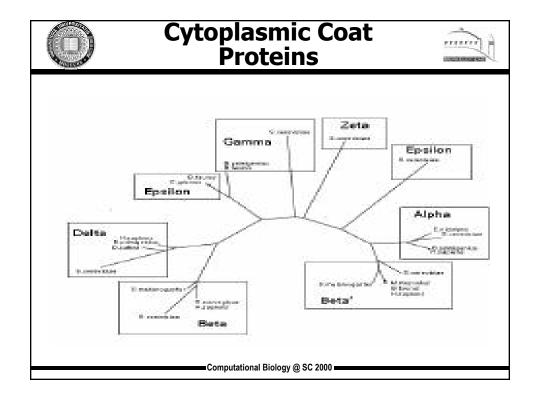




Applications & Interesting examples



- Better understanding of evolution (Ceolocanths, cyanobacterial origin of plastids)
- Maintenance of biodiversity
- Medicine & molecular biology
 - our cousins, the fungi
 - Cytoplasmic coat proteins
 - HIV





HIV



- Where did HIV come from, and how recent is it?
- Korber, et al. 2000. Timing the ancestor of the HIV-1 pandemic strains. Science 288:1789. (Online at www.sciencemag.org/cgi/content/full/288/5472/1789)
- Used completed HIV sequences from 159 individuals with known sampling dates (including one from 1959)
- Used a general-reversible (REV) base substitution model, accounting for different site-specific rates of evolution and base frequencies biased in favor of adenosine. Used modified version of fastDNAml.
- Used SIV as an outgroup
- Last common ancestor of main group of HIV-1 was 1931 (95% confidence interval: 1915-1941). Supports hypothesis that HIV has been around for some time and simply took a while to be common enough to be noticed.

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Challenges for future



- HPC implementations of more phylogenetic techniques
- Better treatment of insertions and deletions (indels)
- Algorithms for more thorough searching of treespaces in incremental tree building processes (keep best n trees and keep looking)
- Techniques for not shaking the whole tree (that is, adding a taxa to a tree in a fashion that acknowledges damping of effect as you travel away from altered part of tree)
- Use of high-throughput techniques



Acknowledgements



- The phylogeny depicted in slide 5 is taken from E. Colbert. 1965. The age of reptiles. W.W. Norton, NY, NY.
- Some of the tree diagrams were adapted from Olsen et al. 1994.
- Les Teach [IU] created all other graphics for this talk
- IU's work on parallel versions of fastDNAml has been facilitated by Shared University Research grants from IBM, Inc.
- IU's work with fastDNAml would be impossible without our collaboration with Gary Olsen, U. of Illinois, the creator of this program.

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- Swofford, D.L., and G.J. Olsen. Phylogeny reconstruction. pp. 411-501
 IN D.M. Nillis & C. Mority (eds). Molecular systematics. Sinauer
 Associates, Sunderland, MA.
- Durbin, R. et al. 1998. Biological sequence analysis. Cambridge University Press, Cambridge, UK.
- www.ucmp.berkely.edu/subway/phylogen
- evolution.genetics.washington.edu/phylip/software
- http://www.indiana.edu/uits/~rac



URLs for phylogenetic software



- Phylip evolution.genetics.washington.edu/phylip/software.html
- PAUP www.lms.si.edu/PAUP/index.html
- PAML abacus.gene.ucl.ac.uk/software/paml.html
- fastDNAml geta.life.uiuc.edu/~gary/

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Specialized biological databases and their role in building models of regulation

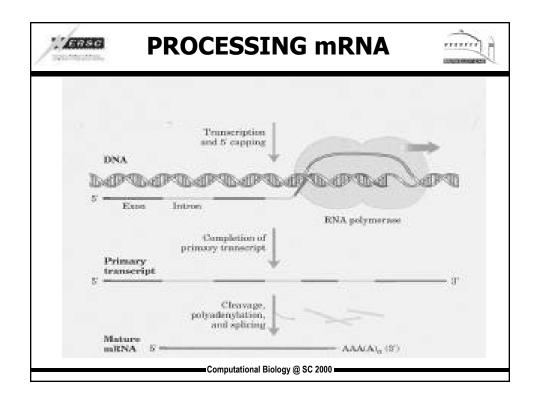
Inna Dubchak ILDubchak@lbl.gov NERSC



Overview of alternative splicing



- What is alternative splicing?
- What is possible to do computationally to better understand this complicated phenomenon?
 - Frequency of alternative splicing
 - Specialized databases
 - Search for regulatory elements





The Nobel Prize in Physiology or Medicine 1993



The Nobel Assembly at the Karolinska Institute in Stockholm, Sweden, has awarded the Nobel Prize in Physiology or Medicine for 1993 jointly to Richard J. Roberts and Phillip A. Sharp for their discovery of split genes.





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Alternative Splicing of a-tropomyocin pre-mRNA Thomas area Splicing Non-march Striated acceptable Striated acceptable Brain Computational Biology @ SC 2000



Gender in Drosophila



- A percursor-RNA may often be matured to mRNAs with alternative structures. An example where alternative splicing has a dramatic consequence is somatic sex determination in the fruit fly Drosophila melanogaster.
- In this system, the female-specific sxl-protein is a key regulator. It controls a cascade of alternative RNA splicing decisions that finally result in female flies.
- Sex in Drosophila is largely determined by alternative splicing



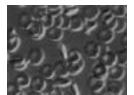
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Splicing and diseases



- Splicing errors cause thalassemia
- Thalassemia, a form of anemia common in the Mediterranian countries, is caused by errors in the splicing process.



Normal red blood cells contain correctly spliced beta-globin, an important component in hemoglobin that takes up oxygen in the lungs.





Information on alternative splicing in public databases:



- Swiss-Prot (protein) database is well curated, but the information content is incomplete with reference to alternative splicing and does not allow for automatic retrieval of such entries.
- Swiss-Prot entries just state the fact that a particular protein is one of the products of alternative splicing.
- Some entries contain the information on the limited number of isoforms.

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Clustering procedure



Similarity analysis of two sequences

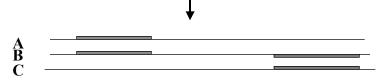
- Gene families multiple similar genes exist due too duplication and divergence of genes.
- Short similar fragments, a lot of mutations
- Alternative splicing one gene but primary transcript spliced in more than one way
- Relatively long identical fragments



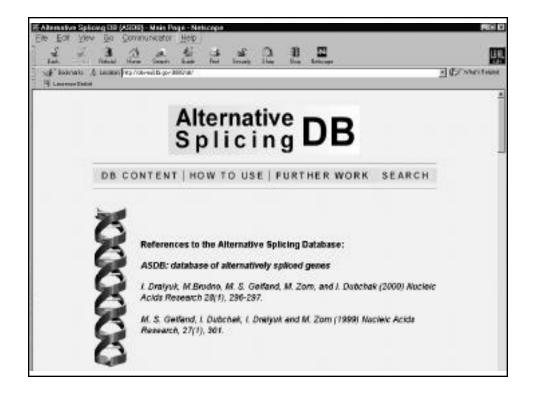
Clustering procedure

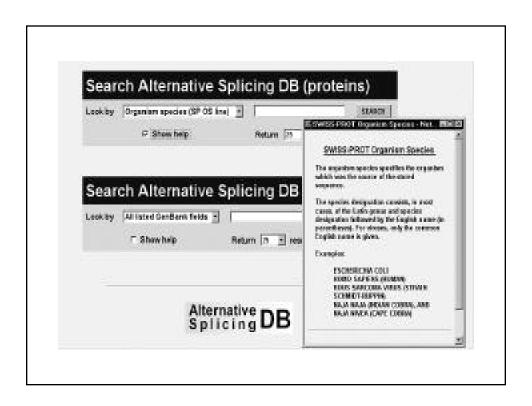


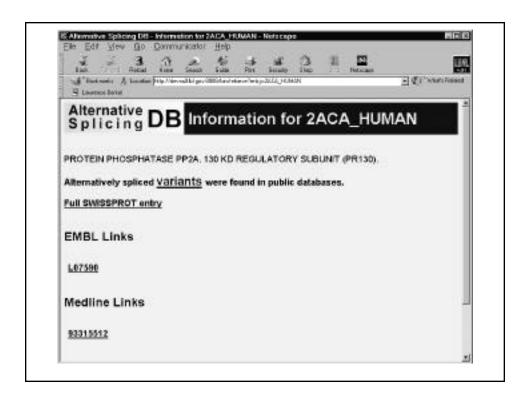
- 1,922 protein sequences were compared all-against-all in order to find common sequence fragments.
- The length of this fragment was a variable parameter in the software. Various lengths were tested to cluster as many variants of the same gene as possible, but to avoid false clusters generated by too short fragments.

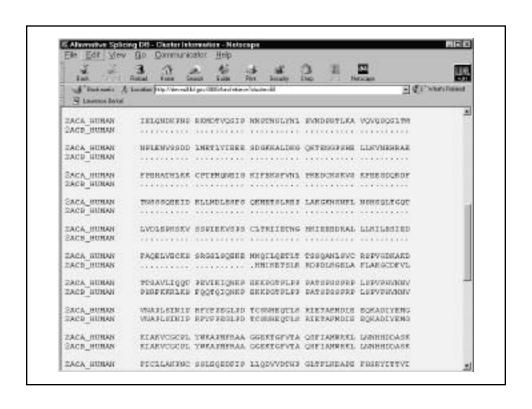


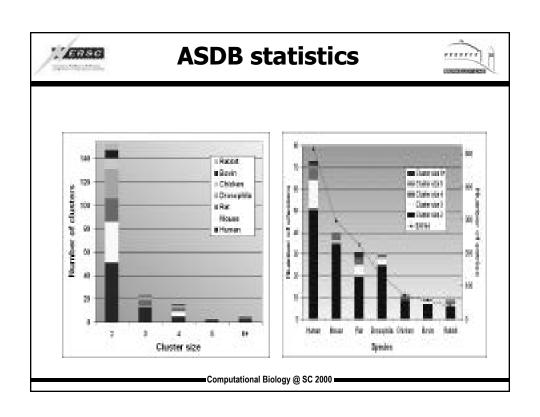
~ 240 clusters of isoforms







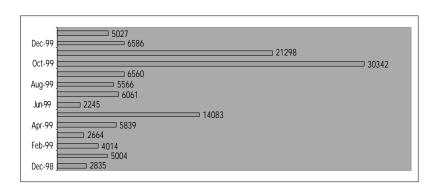






ASDB usage during 1999





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Study of Regulation



- No systematic surveys to address the relative importance of such elements in the regulation of alternative splicing.
- It is unknown as to whether regulatory words occur more frequently adjacent to alternative exons than in the rest of the genome.
- It is not clear whether these elements enhance splicing of only a limited set of exons, or have a more general role.

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Alternative Splicing Regulation



- A number of genomic sequence regulatory elements have been identified outside of traditional splice sites.
- The concept of splicing "enhancers" and "silencers" that promote or inhibit splicing at neighboring splice sites is well established.
- Many alternative exons are probably regulated by a combination of silencers and enhancers.

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Data Collection



- Automated processing of GenBank/Medline
- Manual analysis of abstracts & articles
- **■** Collecting the sample



BiSyCLES Search Options



- BiSyCLES searches in the two databases, then establishes which of the retrieved entries are linked
 - ✓ Medline: +"alternative splicing," tissue, muscle, brain, neuro*, heart, regul*, enhancer, silencer
 - ✓ Genbank: +"alternative splicing" +"complete CDS"
- Results:
 - √ ~300 abstracts
 - √ ~50 relevant papers

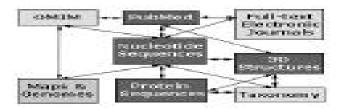
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BiSyCLES: Biological System for Cross-Linked Entry Search



- GenBank contains genomic data but little annotation
- Medline (PubMed) contains abstracts from journals but no genomic data
- NCBI's Entrez system keeps links between related entries in its databases



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Word Counting



- To calculate the confidence value of a particular word we select random subsets of a large dataset of constitutively spliced exons (1,504 exons; Burset & Guigo, 1996) equal in size to our alternative dataset.
- We then calculate the fraction of these subsets in which the word is over-represented at a higher rate than in the alternative set.
- (Over-representation is calculated as difference of frequencies)

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Known Regulatory Elements



<u>enhancers</u>	reference	
UGCAUG	Huh & Hynes, 1994; Hedjran et al., 1997; Modafferi & Black, 1997; Kawamoto, 1996; Carlo et al., 1996	
CUG repeat	Ryan et al., 1996; Philips et al., 1998	
(A/U)GGG	Sirand-Pugnet et al., 1995a	
GGGGCUG	Carlo et al., 1996	
silencers		
UUCUCU	Chan & Black, 1995; Chan & Black, 1997; Ashiya & Grabowski, 1997	



Short summary



- In the simple cases of splicing, introns are always introns and exons are always exons
- During alternative splicing, within the same RNA, sequences can be recognized as either intron or exon under different conditions and the concept of exons and introns becomes rather empirical
- RNAs are not spliced differently in the same cell at the same time but in different cells or in the same cell types at different times in development or under different conditions
- A variety of patterns of alternate splicing have been observed.

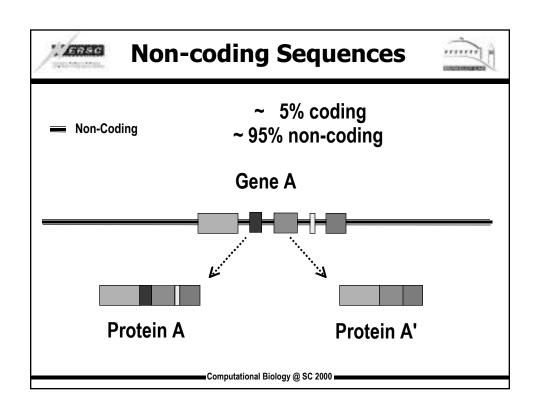
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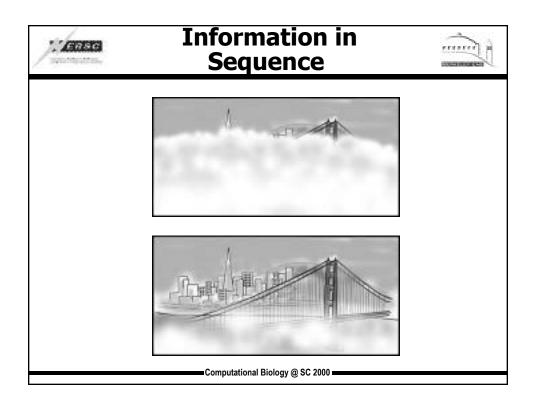
Evolutionarily conserved non-coding DNA sequences

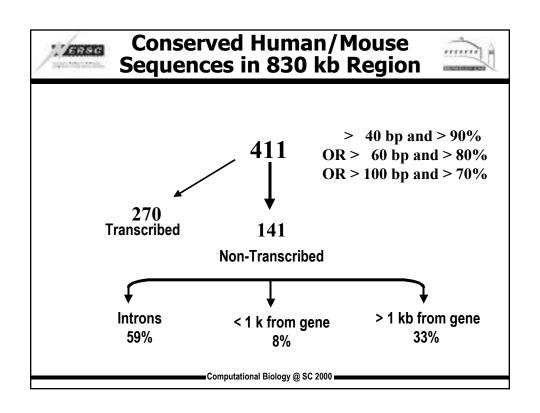


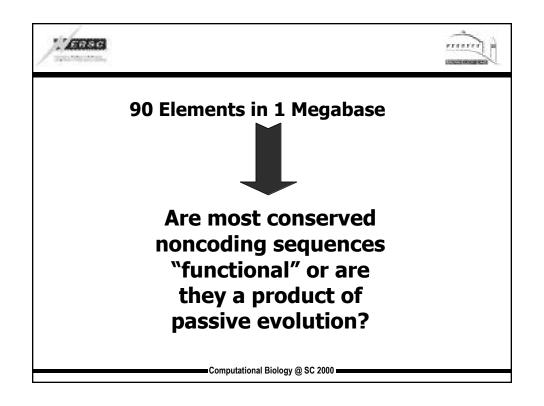
- Discovering them in DNA sequence
- **■** Tools for their visualization
- **■** Biological importance

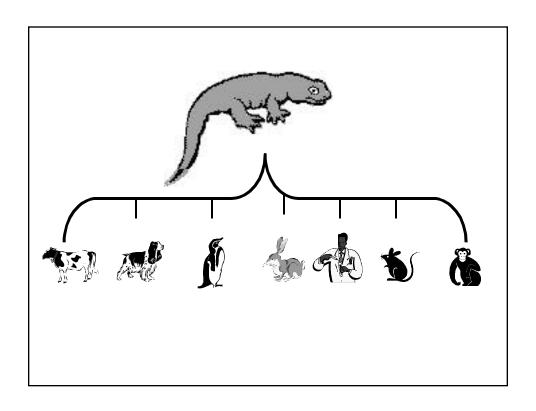
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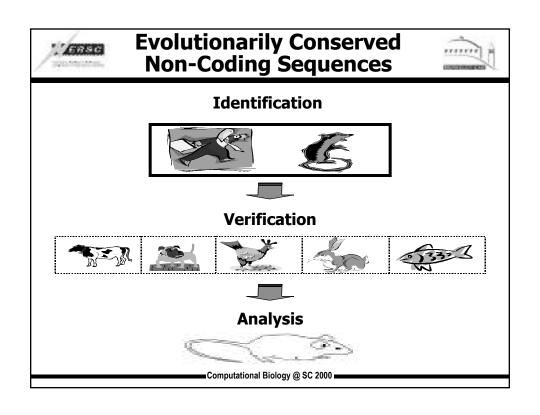
Analysis of CNS-1

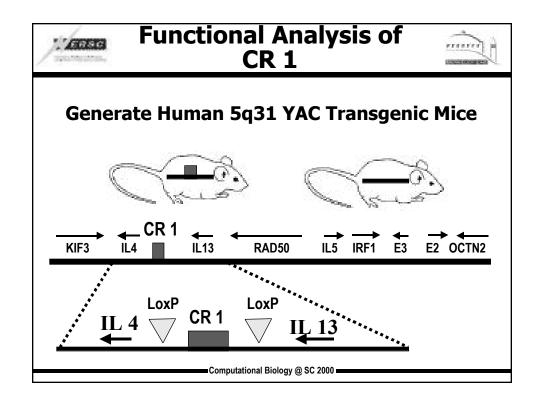


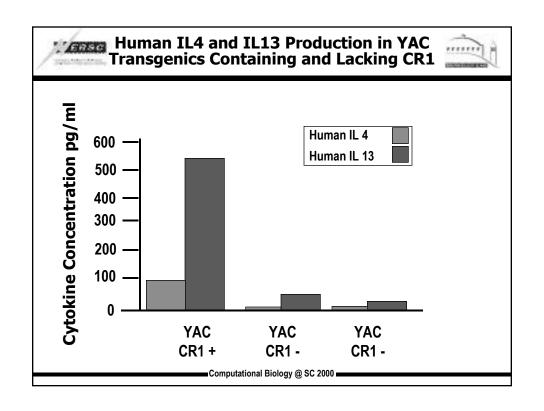
- Present in other species:
 - ◆ Cow (86%)
 - ◆ Dog (81%)
 - ◆ Rabbit (73%)
- Genomic position conserved in human, mouse, dog and baboon

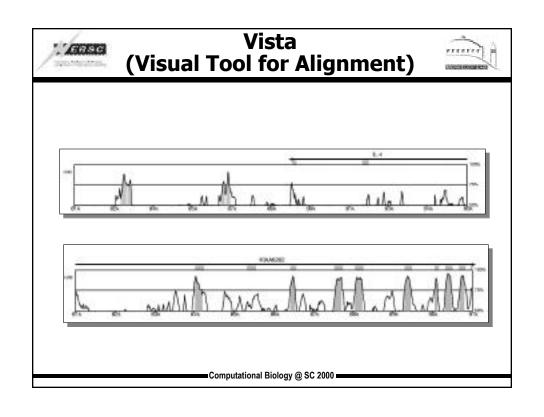


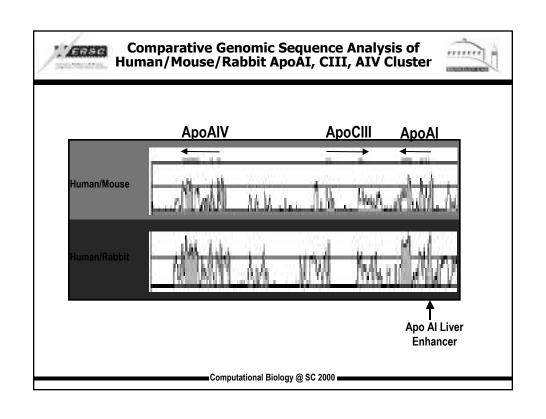
■ Single copy in the human genome

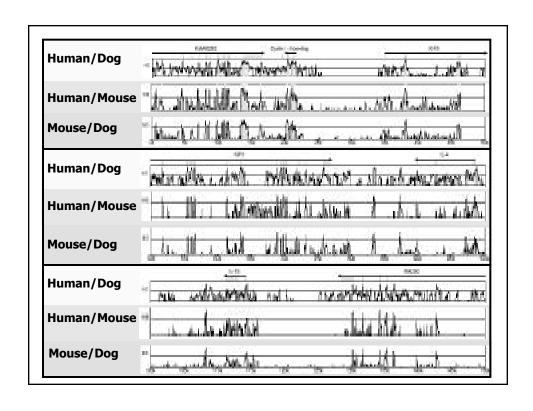


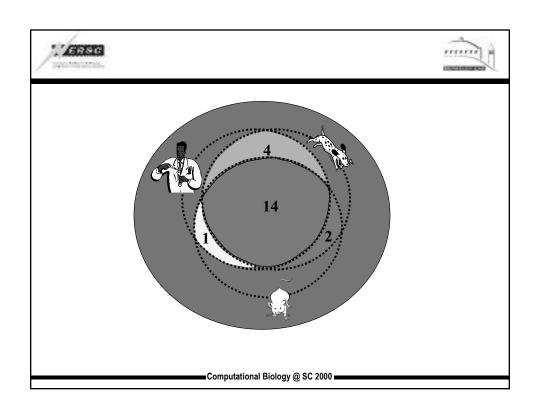


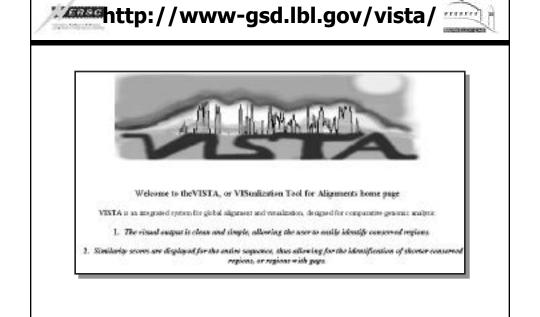














Gene Regulatory Networks and Cellular Processes

Adam Arkin APArkin@lbl.gov LBNL



Engineering of Cellular Circuitry





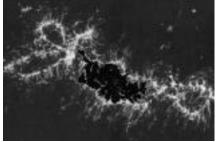
Courtesy of IBM

Asynchronous Digital Telephone Switching Circuit

Full knowledge of parts list Full knowledge of "device physics" Full knowledge of interactions

No one fully understands how this circuit works!! Its just too complicated.

Designed and prototyped on a computer (SPICE analysis) Experimental implementation fault tested on computer



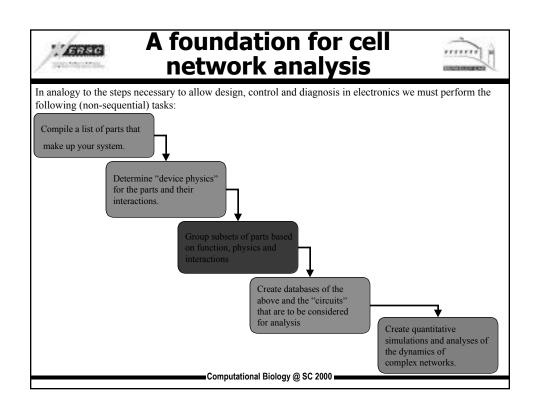
From: Wasserman Lab, Loyola

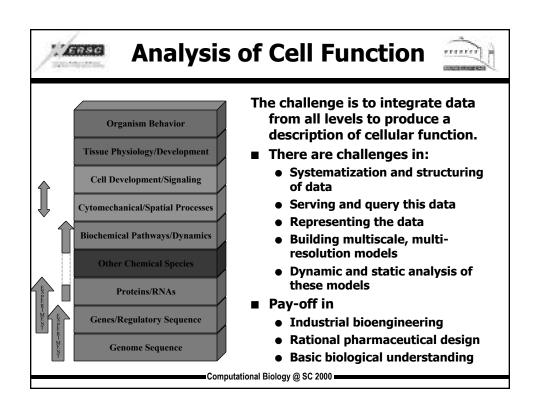
Asynchronous Analog Biological Switching Circuit

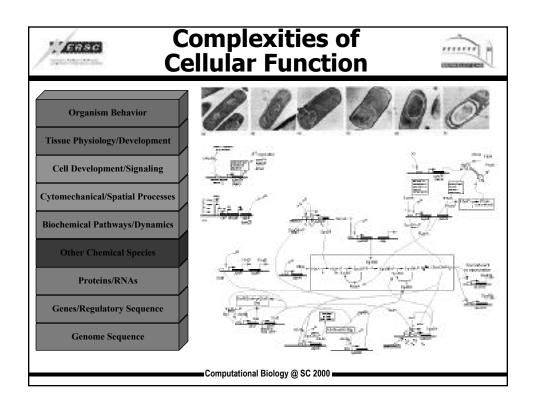
Partial knowledge of parts list Partial knowledge of "device physics" Partial knowledge of interactions

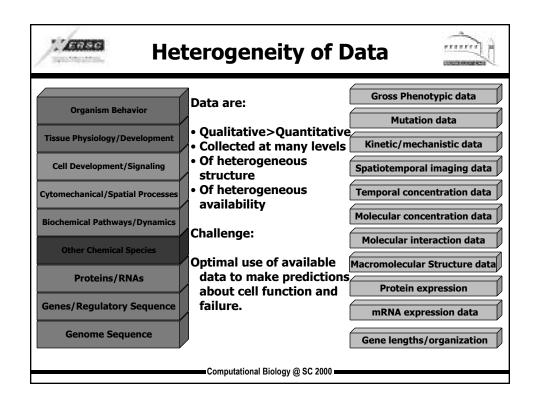
No one fully understands how this circuit works!! Its just too complicated.

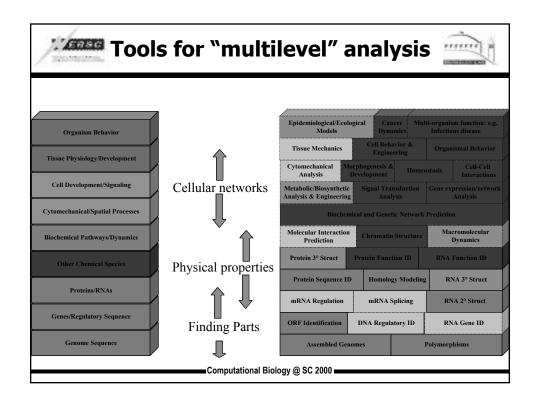
We need a SPICE-like analysis for biological systems









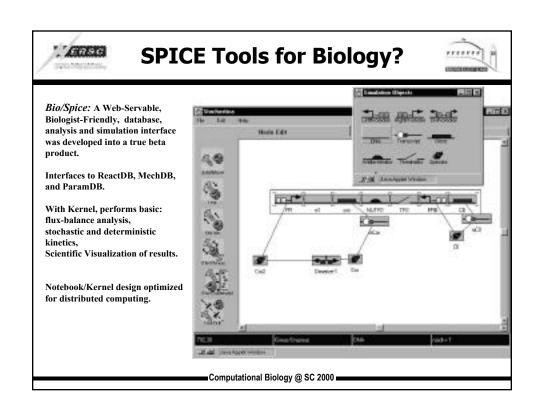


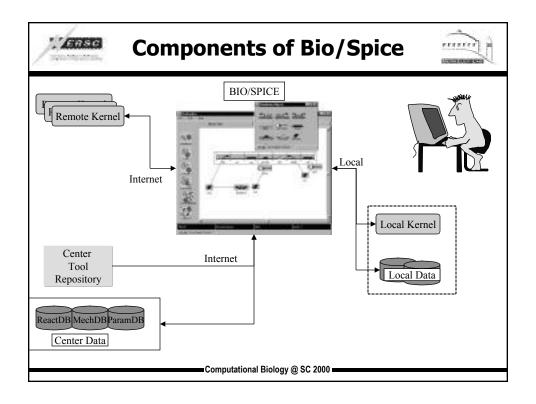


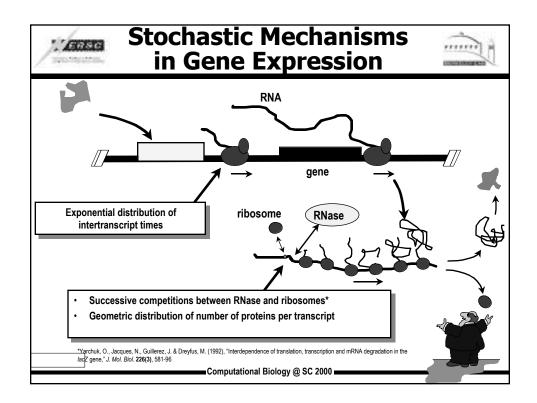
Why now?



- Genome projects are providing a large (but partial) list of parts
- New measurement technologies are helping to identify further components, their interactions, and timings
 - ✓ Gene microarrays
 - ✓ Two-Hybrid library screens
 - High-throughput capillary electrophoresis arrays for DNA, proteins and metabolites
 - ✓ Fluorescent confocal imaging of live biological specimens
 - ✓ High-throughput protein structure determination
- Data is being compiled, systematized, and served at an unprecedented rate
 - ✓ Growth of GenBank and PDB > polynomial
 - $\ensuremath{\boldsymbol{\nu}}$ Proliferation of databases of everything from sequence to confocal images to literature
- The tools for analyzing these various sorts of data are also multiplying at an astounding rate









Some Stochastic Cellular Phenomena



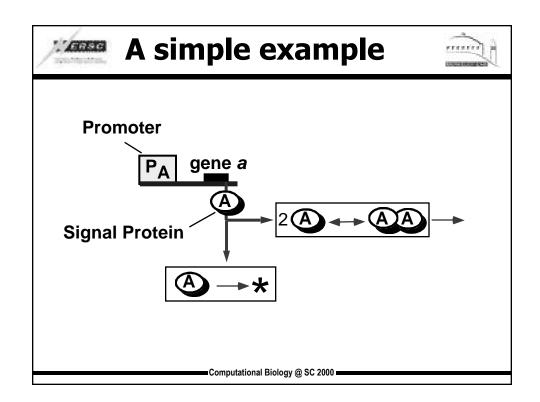
- Lineage commitment in human hemopoiesis
- Random, bimodal eukaryotic gene transcription in
 - Activated T cells
 - Steroid hormone activation of mouse mammary tumor virus
 - HIV-1 virus
- Clonal variation in:
 - Bacterial chemotactic responses
 - Cell cycle timing
- E. coli type-1 pili expression
 - Enhances virulence
- Changing cell surface protein expression
 - For immune response avoidance
- Bacteriophage I lysis/lysogeny decision

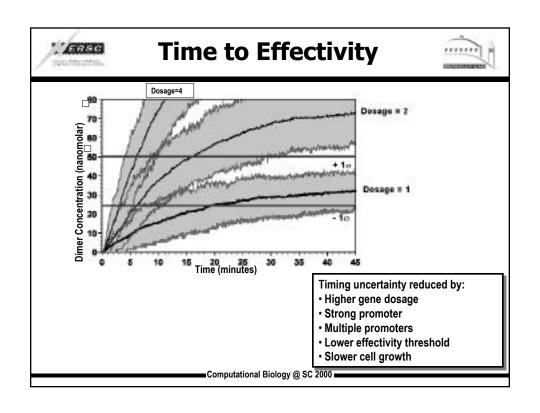


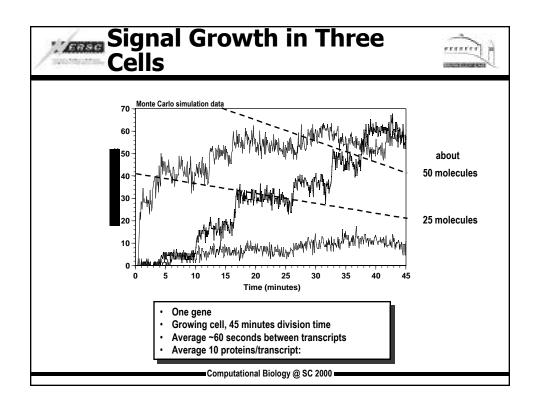
Where Noise Comes From?



- **■** Random environmental influences
- Mutations
- Asymmetric partitioning at cell division
- Stochastic mechanisms in gene expression
 - Stochastic timing of gene expression
 - Random variation in time for signal propagation
 - Random variation total protein production



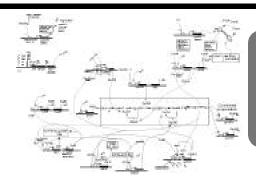






Complexities of Cellular Function





This is approximately 1/3 of just the initiation of the sporulation program from Bacillus subtilis.

There are over 100 proteins, 40 genes, 300 reactions for which data is available.

The total data on just this process is a tens of Gb and it is incomplete. Microarray and microscope data are added 100 Mb per week. Model builders need to query this data and arrange it for simulation. Simulations must be run under many different condition and hypotheses.

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The Need for Advanced Computing



■ Data Handling:

The total data necessary for network analysis is huge. By nature it will be distributed and heterogeneous

We need:

- ✓ Database standard and new query types
- ✓ Means of secure, fast transmission of information
- ✓ Means of quality control on data input

■ Tool integration:

- ✓ Centralization of computational biology tools and standards
- ✓ Ability to use tools together to generate good network hypotheses
- ✓ Good quality ratings on Tool outputs

Advanced Simulation Tools:

- ✓ Fast, distributed algorithms for dynamical simulation
- ✓ Mixed mode systems (differential, Markov, algebraic, logical)
- ✓ Spatially distributed systems

